

## Investigation of trends in extreme value wave height and wind speed

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[1] Global altimeter data spanning a period of more than 20 years is analyzed to determine whether there are measurable trends in extreme value return period estimates of wind speed and wave height. The data is subdivided into sections of 4 years duration and extreme value analysis applied to each section. The trends in values across these sections indicate that there appears to be a positive trend in 100 year return period values of wind speed but no consistent trends for 100 year return period wave height. However, the statistical uncertainty associated with estimates of the extreme value wind speed and wave heights is such that the quantitative values of trend are not reliable. Reliable values will require a longer-duration data set.

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### 1. Introduction

[2] Many oceanographic and engineering applications require estimates of extreme values of geophysical parameters such as wave height and wind speed. Examples include the design of coastal and offshore structures, ship routing and the operation of facilities. Such extremes can be expressed in a number of forms. For a given time series, operational activities will require estimates of extreme individual wave amplitudes or wind gusts. Similarly, statistical quantities such as 99th percentiles signify the values which would be exceeded 1% of the time. For structural design purposes, interest focuses on determination of the return period of extreme events. For instance, the value with a return period of 100 years could be expected to be exceeded, on average, once every 100 years. It is these extreme value return period estimates which are the subject of this paper. As observational data spanning periods as long as 100 years are seldom available, it is typically necessary to estimate such extreme values from a shorter time series based on estimates of the underlying probability distribution function. A basic assumption in such analyses is that the time series is stationary. Under this assumption it is possible to extrapolate from the finite duration time series to more extreme events. However, if oceanographic wave and wind climates are changing on decadal time scales then estimates of extreme values based on such analyses may be in error.

[3] Studies of global wind and wave conditions provide evidence that in recent decades mean and extreme conditions (90th and 99th percentile values) may have increased [e.g., Gulev and Hasse, 1998, 1999; Wentz *et al.*, 2007; Thomas *et al.*, 2008; Tokinaga and Xie, 2011; Young *et al.*, 2011a]. If such conditions have increased, then it is possible that extreme value estimates of wave height and wind speed may also have changed. Understanding the potential magnitude of such changes is important for the applications outlined above. For instance, the design of coastal and offshore structures may be inadequate if extreme values of wave height and wind speed are increasing.

[4] Global data sets of remote sensing satellite data are now available over multiple decades and have been used to estimate climatology [e.g., Young, 1994, 1999; Young and Holland, 1996], extreme value return period wave height and wind speed [e.g., Alves and Young, 2003; Chen *et al.*, 2004; Panchang *et al.*, 1998; Vinoth, 2011; Vinoth and Young, 2011] and trends in mean and percentile values [Wentz *et al.*, 2007; Tokinaga and Xie, 2011; Young *et al.*, 2011a]. This paper analyses the long-term altimeter data sets to investigate whether statistically significant trends in extreme value (i.e., 100 year return period) wave height and wind speed have occurred over this period.

[5] The arrangement of the paper is as follows. Section 2 reviews techniques used to determine extreme value estimates, particularly applied to wave height and wind speed. Section 2 also reviews the previous attempts to investigate trends in extreme value estimates. This is followed in section 3 by a review of global data sets which are suitable for the investigation of extreme value determination. Section 4 investigates previous studies of trends in wind speed and wave height. Analysis of the global altimeter data set for wave height and wind speed to determine trends is presented

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in section 5 together with validation studies. Finally, conclusions are reported in section 6.

## 2. Extreme Values Estimation Techniques

### 2.1. Probability Distributions

[6] From a sample of measured data, the aim is to determine the probability distribution function (PDF),  $P_x(x)$  which represents the data [Gumbel, 1958]. Although it is desirable to represent the full PDF, as the aim is to determine the probability of extreme events, the focus is often confined to the extreme tail of the distribution. Three approaches are commonly used: the initial distribution method (IDM), the annual maximum method (AMM), and the peaks over threshold method (POT).

[7] The IDM uses all available data and fits a Cumulative Distribution Function (CDF) to the data. As the bulk of the data used to fit the CDF comes from “moderate” rather than extreme conditions, the IDM is biased to the body of the CDF. As such, it is important that the form of the CDF is capable of also reproducing extreme conditions, where there will be relatively few observations compared to the body of the distribution. There is no theoretical approach to determine the most appropriate CDF for such an application, and a number of forms have been proposed [see Tucker, 1991; Goda, 1988]. Commonly used candidates are the Fisher-Tippett Type 1 (FT-1) or Gumbel, the Weibull two-parameter, and the Weibull three-parameter distributions. Alves and Young [2003] and Vinoth and Young [2011] have investigated these forms with altimeter data, finding the FT-1 distribution gives reliable results

$$F(x) = \exp \left[ - \exp \left( - \frac{x-A}{B} \right) \right], \quad (1)$$

where  $F(x)$  is the CDF of the variable  $x$  and  $A$  and  $B$  are parameters determined by the fitting process. The variable  $x$  in the present context takes on the values of significant wave height,  $H_s$ , or wind speed,  $U_{10}$ .

[8] As outlined by Gumbel [1958], to form a valid distribution, observations should be independent and identically distributed. That is, successive observations should not be serially correlated with one another. Such a correlation would occur if successive observations are obtained from the same meteorologic event. When using buoy data, with observations at a 3 hourly interval, this clearly becomes an issue. In the case of remote sensing data (e.g., altimeter), however, successive observations may be days apart and independence of observation is not a significant issue [see Vinoth and Young, 2011].

[9] Despite the limitations of the IDM, it has been successfully applied to both buoy and altimeter data [see, e.g., Goda, 1992, 1988; Ochi, 1992; Tucker, 1991; Alves and Young, 2003; Vinoth and Young, 2011].

[10] The AMM attempts to address both the issue of independence of observations and the focus on the extreme tail of the distribution by considering only the largest observation in a 12 month period. In these circumstances, it can be shown that the maxima will follow a generalized extreme value distribution [Castillo, 1988]. Although the AMM has a sound theoretical basis, as only one observation is available each year, the available time series are

typically very short and hence the CDF can typically not be determined accurately. As such, the AMM is generally not practical for oceanographic applications.

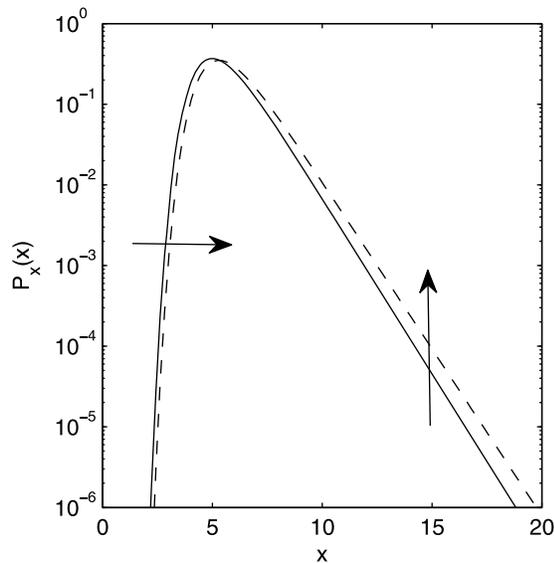
[11] The POT method attempts to address the practical shortcomings of the AMM by defining an arbitrary threshold intended to separate moderate conditions from storm events. The method then considers the “peak” value in each rise and fall of the observed data above the threshold. That is, one observation from each storm event. Extreme value theory [Castillo, 1988; Coles, 2001] indicates that the distribution of the maxima in such a situation will follow a Generalized Pareto Distribution (GPD). Although not having the same theoretical basis, the Weibull 3 parameter distribution (W3P) has also been fitted to such data [Guedes Soares and Henriques, 1996].

[12] Although the POT approach has a strong theoretical basis, selection of the arbitrary threshold value is a significant shortcoming. As shown by Coles [2001], there is no theoretical approach to its selection. In addition, the CDF and hence extreme value estimates are sensitive to the choice of the threshold [Vinoth and Young, 2011]. The POT approach has been extensively applied to buoy data [e.g., Goda, 1992; Van Gelder and Vrijling, 1999; Ferreira and Guedes Soares, 1998]. Applications to satellite (altimeter) data [Caires and Sterl, 2005; Challenor et al., 2004; Alves and Young, 2003; Vinoth and Young, 2011] indicate that the approach is sensitive to under sampling. As satellite observations at a point are typically separated by of order 10 days, many storm events are not observed. As such, the POT approach tends to yield results with significant spatial variability caused by the small number of “peaks” in typical time series. Vinoth and Young [2011] have, however, shown that with the longer time series (23 years) now available for altimeter data, stable results can be obtained using the POT approach applied to  $H_s$ . However, wind speed exhibits greater spatial variability than wave height and hence POT estimates of extreme value  $U_{10}$  produce unacceptable data scatter when applied to the presently available combined altimeter data set. This issue will decrease as the length of the available time series increases in future years.

[13] As outlined below, the approach to be adopted here is to investigate trends in extreme values by subdividing the available observational altimeter database into shorter blocks and determining extreme value estimates for such periods. Obviously, as the length of the record decreases, the potential error (confidence interval) for the prediction increases. This approach means that neither the AMM nor the POT is a practical candidate. Fortunately, the IDM is relatively insensitive to the length of the data set. As shown by Vinoth and Young [2011], little improvement in predicted results has occurred by increasing the length of the available data set from less than 10 years to more than 20. As a result, the IDM approach with the FT-1 distribution has been adopted for the remainder of this study.

### 2.2. Goodness of Fit and Confidence Limits

[14] A key element in the application of these approaches is how well the selected CDF fits that observed data. The “goodness of fit” to the data can be determined from the residual between the empirical distribution function, EDF (i.e., the CDF obtained from the recorded data) and the theoretical CDF chosen to fit the data. Three general approaches



**Figure 1.** A typical example of a probability density function,  $P_x(x)$  (the FT-1 is shown). An increase in the mean will move the distribution to the right, elevating the tail of the distribution. An increase in the variance will also elevate the tail of the distribution. In both cases, the elevated tail of the distribution would result in larger values of  $x$  at extreme probability levels.

have been proposed to determine the goodness of fit [see *Vinoth and Young, 2011*].

[15] Supremum statistics [*Stephens, 1986*] consider the largest positive and negative differences between the EDF and the CDF. This is typically termed the Kolmogorov-Smirnov test. Alternatively, (quadratic statistics) the sum of the squares of the differences between the EDF and the CDF define either the Cramér-von Mises or Anderson and Darling test [*Anderson and Darling, 1952*] statistic depending on the weighting applied to the squared difference.

[16] *Goda and Kobune [1990]* proposed an alternative approach where they consider the value of the correlation coefficient relating the observed data and its reduced variate (i.e., the CDF expressed in a linear form). The closer the value of the correlation coefficient to the value one, the better the chosen CDF approximates the observed data. Tabulated values to calculate this approach are given by *Goda [2000]* as well as confidence limits based on the same approach.

[17] As interest is generally confined to the extreme value tail of the distribution, the above approaches can all be modified to consider only that part of the CDF above some limit. For instance, if only the top 20% of values are considered, the test is usually referred to as having been censored at the 20% level [*Stephens, 1986*].

### 2.3. Extreme Value Trends

[18] There are very few studies which have attempted to examine trends in oceanographic extremes. As outlined above, determination of extreme value statistics requires a relatively long time series to accurately determine the CDF. In order to determine whether the CDF is changing as a function of time requires an even longer data set. Figure 1

shows a typical PDF of wave or wind conditions (FT-1 distribution). An increase in the mean and/or the variance of the distribution can potentially elevate the tail of the distribution, increasing the probability of extreme events. That is, in such a situation, the values of the 100 year event would increase.

[19] *Günther et al. [1998]* and *Caires and Sterl [2005]* have considered wave model hindcasts of approximately 40 years duration to investigate trends in the 100 year return period wave height. In both cases, the full time series was divided into 10 year segments and the POT method applied to each segment to determine the 100 year return period significant wave height,  $H_s^{100}$ . Both studies showed evidence of positive trends in  $H_s^{100}$ , although regional variations were also evident. In addition, there appeared to be correlations with decade-scale climate variations such as the Northern Oscillation Index.

## 3. Global Data Sets

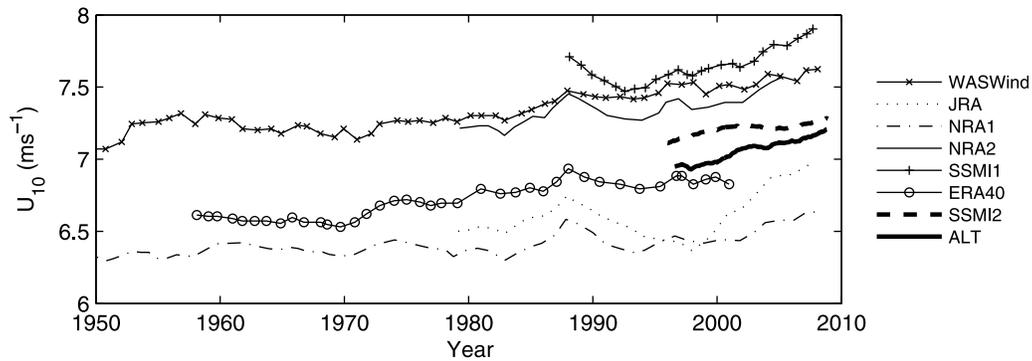
[20] There are a number of potential data sources of wave and wind data on a global or almost global scale. These data sets include the following: Satellite data include (1) altimeter data for wind speed and wave height spanning more than 20 years, (2) scatterometer data of wind speed spanning approximately 20 years (not presently compiled into a single data base), (3) Special Sensor Microwave Imager (SSM/I) data of wind speed spanning more than 20 years, and (4) synthetic aperture radar (SAR) data of the directional wave spectrum (images exist over a more than 20 year period but not compiled as a single data base). Model data include reanalysis data from both Wave Model (WAM) and WAVEWATCH Models over a period up to 40 years. Other data sources include (1) offshore data buoy networks of wind speed and wave height dating back more than 30 years (only at point locations), (2) microseism data of wave height dating back more than 50 years (only at point locations), and (3) visual observations of wind speed and wave height from ships (data over more than 100 years; confined to shipping routes and of variable quality).

[21] Of the data sets summarized above, the only candidates which provide both wave and wind data over the full globe are the model sources and the altimeter data set. In addition, SSM/I provides wind data on a global scale. A number of the other data sets provide potential validation sources (e.g., buoys, microseism, and ship observation data). As the focus here is on measured data rather than model predictions, the altimeter data set has been adopted as the primary data set for this study.

## 4. Observed Trends in Wind Speed and Wave Height

### 4.1. Wind Speed

[22] There are four data sources which have commonly been used to assess long-term trends in wind speed: ship observations, in situ anemometers, model reanalysis studies, and satellite remote sensing data. Records obtained from ship reports (International Comprehensive Ocean-Atmosphere Data Set) [*Worley et al., 2005*] indicate a positive trend in mean wind speed since the 1940s [*Cardone et al., 1990*; *Thomas et al., 2008*]. This trend has, however, largely been



**Figure 2.** The average global wind speed as a function of time for a number of different data sets. The WASWind, JRA, NRA1, NRA2, SSMI1, and ERA40 results have been digitized from *Tokenaga and Xie* [2011]. In addition, the altimeter data (ALT) and SSM/I (SSMI2) results from *Young et al.* [2011a, 2011b] are also shown.

attributed to changes in the manner in which visual estimates have been made and to changes in the height of anemometer measurements [Peterson and Hasse, 1987; Ramage, 1984]. *Thomas et al.* [2008] adjusted the records for these effects and found a positive trend up to  $0.10 \text{ ms}^{-1}\text{decade}^{-1}$  (1950–2004). *Tokenaga and Xie* [2011] further analyzed these data to develop the Wave and Anemometer-Based Sea Surface Wind (WASWind) archive and determined “global” average mean wind speed trends of  $0.084 \text{ ms}^{-1}\text{decade}^{-1}$  (1988–2008) and  $0.107 \text{ ms}^{-1}\text{decade}^{-1}$  (1979–2008). Note that there is no WASWind data in the Southern Ocean and hence this region is excluded from the “global” average.

[23] *Gower* [2002] considered buoy stations across the North Pacific and determined wind speed trends ranging from  $-0.02 \text{ ms}^{-1}\text{decade}^{-1}$  to  $0.35 \text{ ms}^{-1}\text{decade}^{-1}$  (1977–2000), depending on the location. However, as noted by *Gower* [2002] changes in buoy type and anemometer height impacted on the reliability of the data.

[24] *Tokenaga and Xie* [2011] also considered four reanalysis data sets: National Centers for Environmental Prediction (NCEP)/National Center for Atmospheric Research Reanalysis (NRA1) [Kalnay et al., 1996], NCEP-Department of Energy Reanalysis 2 (NRA2) [Kanamitsu et al., 2002], European Centre for Medium-Range Weather Forecasts 40 Year Re-Analysis (ERA40) [Uppala et al., 2006], and the Japanese Reanalysis (JRA) [Onogi et al., 2007]. All four reanalysis data sets showed positive trends in the average “global” wind speed (note that the average does not include the Southern Ocean): NRA1,  $0.066 \text{ ms}^{-1}\text{decade}^{-1}$  (1988–2008); NRA2,  $0.120 \text{ ms}^{-1}\text{decade}^{-1}$  (1988–2008); ERA40,  $0.081 \text{ ms}^{-1}\text{decade}^{-1}$  (1958–2001); JRA,  $0.171 \text{ ms}^{-1}\text{decade}^{-1}$  (1988–2008). *Young et al.* [2011a] also considered the NCEP reanalysis [Kalnay et al., 1996] obtaining a global average mean wind speed trend of  $0.108 \text{ ms}^{-1}\text{decade}^{-1}$  (1992–2009).

[25] *Wentz et al.* [2007] considered SSM/I satellite data to obtain a global average mean wind speed trend of  $0.08 \text{ ms}^{-1}\text{decade}^{-1}$  (1987–2006). *Tokenaga and Xie* [2011] considered this same data set to obtain a trend of  $0.134 \text{ ms}^{-1}\text{decade}^{-1}$  (1988–2008). The difference is presumably due to a combination of the different period for the analysis, different trend extract techniques and the fact that *Tokenaga and Xie* [2011] did not consider data from the

Southern Ocean. *Young et al.* [2011b] considered altimeter data obtaining a larger global average mean wind speed trend of  $0.192 \text{ ms}^{-1}\text{decade}^{-1}$  (1991–2008), which was consistent with limited buoy data used for validation.

[26] These studies obtained from a number of observation methods show a consistent positive trend over recent decades with the global average mean wind speed trend in the range  $0.06$  to  $0.20 \text{ ms}^{-1}\text{decade}^{-1}$ .

[27] Figure 2 shows the variation in the average global mean wind speed as a function of time for a number of the data sets mentioned above. The WASWind, JRA, NRA1, NRA2, SSMI1, and ERA40 results have been digitized from *Tokenaga and Xie* [2011]. In addition, the altimeter data (ALT) and SSM/I (SSMI2) results from *Young et al.* [2011a, 2011b] are also shown. The different data sets show mean values varying by approximately  $\pm 0.5 \text{ ms}^{-1}$ . As details of the averaging processes used to determine the values are not available, the reason for these differences is not clear. However, variations of this magnitude can result due to different methods of forming the average. One can either average over all latitude/longitude grid squares or determine the surface area of the Earth associated with each square and average over the surface area. The former approach will yield larger values as it gives greater weight to the high wind speed areas at high latitudes. The ALT and SSMI2 results were determined by averaging over the surface area of the Earth, which seems the most appropriate approach. In addition, the seasonal signal was removed from these data sets with a 5 year running average. Despite the differences in the mean values, all the data sets show a positive trend in the global average mean wind speed. Also, visual inspection confirms that the rate of increase is larger in more recent years.

[28] There are far fewer analyses of trends for extreme values than for mean conditions. This is largely due to the challenges in obtaining reliable data for extremes. As pointed out by *Young et al.* [2011a] such analyses require both long-duration time series and an observation frequency which enables sufficient extremes to be measured. Under-sampling means that short-duration extreme events may be omitted in the data set. In addition, changes in sampling frequency over the long-duration time series may also bias results by observing more extreme events in periods when

the sampling frequency is high. As noted above, two broad approaches have been adopted. The first is to estimate extreme percentile values based on actual observations of extreme events. The second is to estimate the PDF for the distribution and then extrapolate to the extreme value tail of the distribution. Both approaches have their limitations: percentiles limited by the frequency of the observations, and PDF extrapolation by the accuracy with which the extreme value tail of the PDF can be estimated from a finite duration time series.

[29] The *Günther et al.* [1998] WASA model reanalysis data investigated trends in extreme wind speeds for the northeast Atlantic. They found small increases in extreme values ( $0.032 \text{ ms}^{-1}\text{decade}^{-1}$  for 99th percentile and  $0.026 \text{ ms}^{-1}\text{decade}^{-1}$  for 90th percentile) over the period 1955–1994. *Cox and Swail* [2001] analyzed NCEP data and found that regions of the globe which had positive trends in the mean wind speed had stronger trends in the extreme values (90th and 99th percentiles). *Sterl and Caires* [2005] considered the ERA40 reanalysis (1971–2000) finding maximum trends of  $0.12 \text{ ms}^{-1}\text{decade}^{-1}$  for the 99th percentile in the equatorial regions (approximately twice the magnitude of their mean trend). *Sterl and Caires* [2005] also considered the 100 year return period wind speed, obtained using the POT method and consecutive decadal data blocks. Again, they found increasing trends in the equatorial regions.

[30] *Young et al.* [2011a] found that the altimeter data set showed an increasing global trend at extreme values. The global average trends obtained from the *Young et al.* [2011a] data set are  $0.35 \text{ ms}^{-1}\text{decade}^{-1}$  for 90th percentile and  $0.72 \text{ ms}^{-1}\text{decade}^{-1}$  for the 99th percentile (1991–2008) (cf.  $0.19 \text{ ms}^{-1}\text{decade}^{-1}$  for the mean) (1991–2008). In relative terms, the trend also increases for the more extreme events (2.7% per decade at the mean, 3.6% per decade for the 90th percentile and 6.5% per decade for the 99th percentile).

#### 4.2. Wave Height

[31] As with wind speed, studies of trends in wave height can be classified according to the data sources used: ship observations, in situ data, remote sensing and model reanalysis studies. An extensive series of ship observations over the last 30 years (1964–1993) focused on the North Atlantic were conducted by *Gulev and Hasse* [1998, 1999] and *Gulev et al.* [1998] over the period 1979–1993. They report trends in the mean wave height of between 0.1 and 0.3 m decade<sup>-1</sup>. More recently, *Gulev and Grigorieva* [2004] studied over 100 years of ship observations, reporting slightly lower mean wave height trends of approximately  $0.14 \text{ m decade}^{-1}$  for the North Atlantic and  $0.08\text{--}0.1 \text{ m decade}^{-1}$  for the North Pacific. *Neu* [1984] and *Bouws et al.* [1996] analyzed synoptic charts issued by the Meteorological and Oceanographic Center (Canada) for the North Atlantic and largely based on ship observations. They found a trend in average wave height of  $0.23 \text{ m decade}^{-1}$  (1970–1982) whereas *Neu* [1984] reported larger values between 0.6 and  $1.4 \text{ m decade}^{-1}$  (1960–1985).

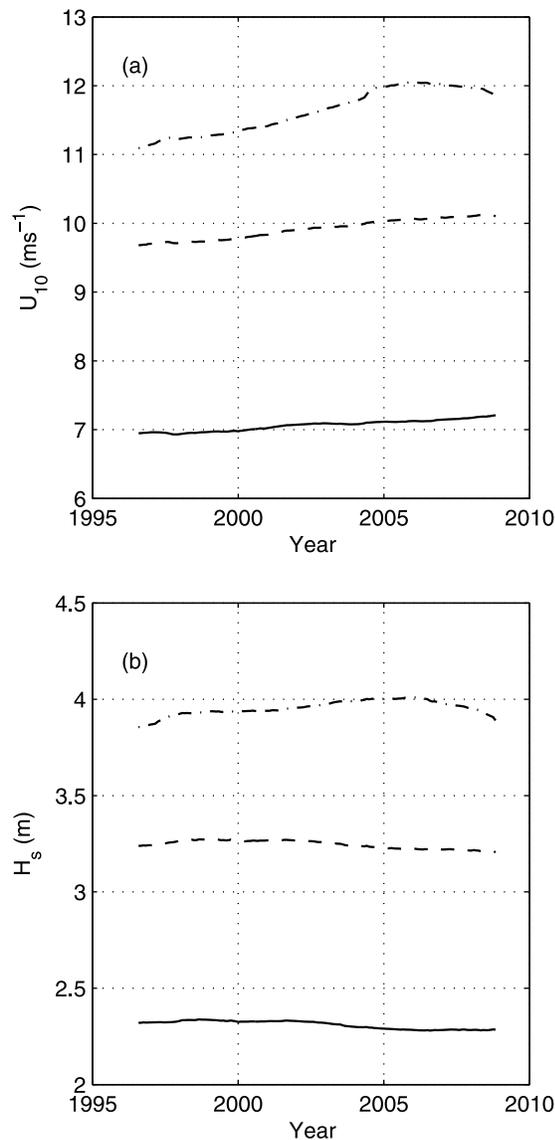
[32] *Bacon and Carter* [1991] analyzed in situ data from two separate locations in the North Atlantic (1961–1986 and 1975–1988). Both showed an increase in average wave

height of approximately  $2\% \text{ yr}^{-1}$ . However, evidence for a change in extreme conditions was less clear due to insufficient data. In a similar fashion, *Gower* [2002] analyzed data from 26 buoys in the North Pacific and found trends in mean significant wave height between  $0.1$  and  $0.24 \text{ m decade}^{-1}$  (1977–1999). More recent studies of buoy data in the North Pacific have shown trends in average significant wave height between  $0.05$  and  $0.27 \text{ m decade}^{-1}$  over the past 20 years (longest duration: 1975–1999) [*Allan and Komar*, 2000] and  $0.15 \text{ m decade}^{-1}$  for the period 1976–2007 [*Ruggiero et al.*, 2010]. *Ruggiero et al.* [2010] found a higher rate of increase in winter, suggesting extremes are increasing at a faster rate than the mean.

[33] Numerous studies have used wave model reanalysis studies to investigate trends in significant wave height. *Günther et al.* [1998] found gradually increasing trends in the North Atlantic for increasing extreme value significant wave height for the period 1955–1994 ( $0.025\text{--}0.075 \text{ m decade}^{-1}$  for mean,  $0.1\text{--}0.2 \text{ m decade}^{-1}$  for the 90th percentile and  $0.3\text{--}0.4 \text{ m decade}^{-1}$  for the 99th percentile). *Sterl et al.* [1998] analyzed the relatively short period from 1979 to 1993 and found positive trends only in winter months as large as  $1.2 \text{ m decade}^{-1}$ . A number of studies have run full spectral wave models with reanalysis wind fields [*Wang and Swail*, 2001, 2002; *Cox and Swail*, 2001; *Sterl and Caires*, 2005; *Wolf and Woolf*, 2006]. These analyses do not show overall global positive trends, although there are significant regions where positive trends exist. They tend, however, to show more positive trends in winter months, again suggesting larger positive trends for extreme conditions. Recently, *Reguero et al.* [2011] have considered a long-duration reanalysis study using the WAVEWATCH 3 model (1948–2010), finding positive trends in the 90th percentile significant wave height between  $0.1$  and  $0.25 \text{ m decade}^{-1}$ . The largest positive trends were in the Southern Ocean.

[34] Because of the limited length of remote sensing data, few studies have considered trends in significant wave height using remote sensing data. *Woolf et al.* [2003] considered 6 years of altimeter data (1992–1998) for the North Atlantic finding positive trends similar to the above studies. *Hemer et al.* [2010] considered altimeter data for the Southern Ocean, and correlated changes in the wave height climate with interannual variability of atmospheric circulation. More recently, *Young et al.* [2011a] considered 23 years of altimeter data (1991–2008), finding trends becoming more positive at more extreme values (e.g., 99th percentile). When averaged over the whole globe, however, the trends are relatively neutral ( $-0.04 \text{ m decade}^{-1}$ : mean,  $-0.04 \text{ m decade}^{-1}$ : 90th percentile,  $0.07 \text{ m decade}^{-1}$ : 99th percentile).

[35] Figure 3a shows the global average values of the mean, 90th percentile and 99th percentile wind speed as a function of time for the altimeter data set reported by *Young et al.* [2011a]. The seasonal signal was removed with a 5 year running average. The clear positive trend is evident in each of the quantities, with the magnitude of the trend increasing for the more extreme percentiles. The corresponding time series for wave height is shown in Figure 3b. As indicated above the trends are less clear with the mean and 90th percentile decreasing slightly over the period and the 99th percentile showing an overall positive



**Figure 3.** The average global mean (solid line), 90th percentile (dashed line) and 99th percentile (dash-dotted line) (a) winds speed and (b) wave height as a function of time. The altimeter data of *Young et al.* [2011a] is shown.

trend, but with evidence of a decrease in more recent years (since 2006).

## 5. Extreme Value Trend Estimates

[36] The present analysis seeks to investigate trends in the 100 year return period values of both wind speed and wave height. Although this could be done using reanalysis model results, this brings with it the uncertainty of model physics and changes in the accuracy of wind and pressure fields over an extended period. Hence, measured quantities are the preferred data source, the only possibility being remote sensing data. Although long-term (greater than 20 years) wind speed data is available from the SSM/I [Wentz et al., 2007; Tokinaga and Xie, 2011], the only source of both wind speed and wave height data over such a period is provided by altimeter missions.

[37] *Zieger et al.* [2009] compiled an altimeter data set spanning approximately 23 years (1991–2008) from a total of 7 altimeter missions. The data was carefully calibrated against buoy data and validated during periods when multiple altimeters were in operation. The data set has been used to investigate trends in mean, 90th and 99th percentile values of wind speed and wave height by *Young et al.* [2011a] and to determine 100 year extreme value return period estimates by *Vinoth and Young* [2011]. This same data set has been selected for the present analysis.

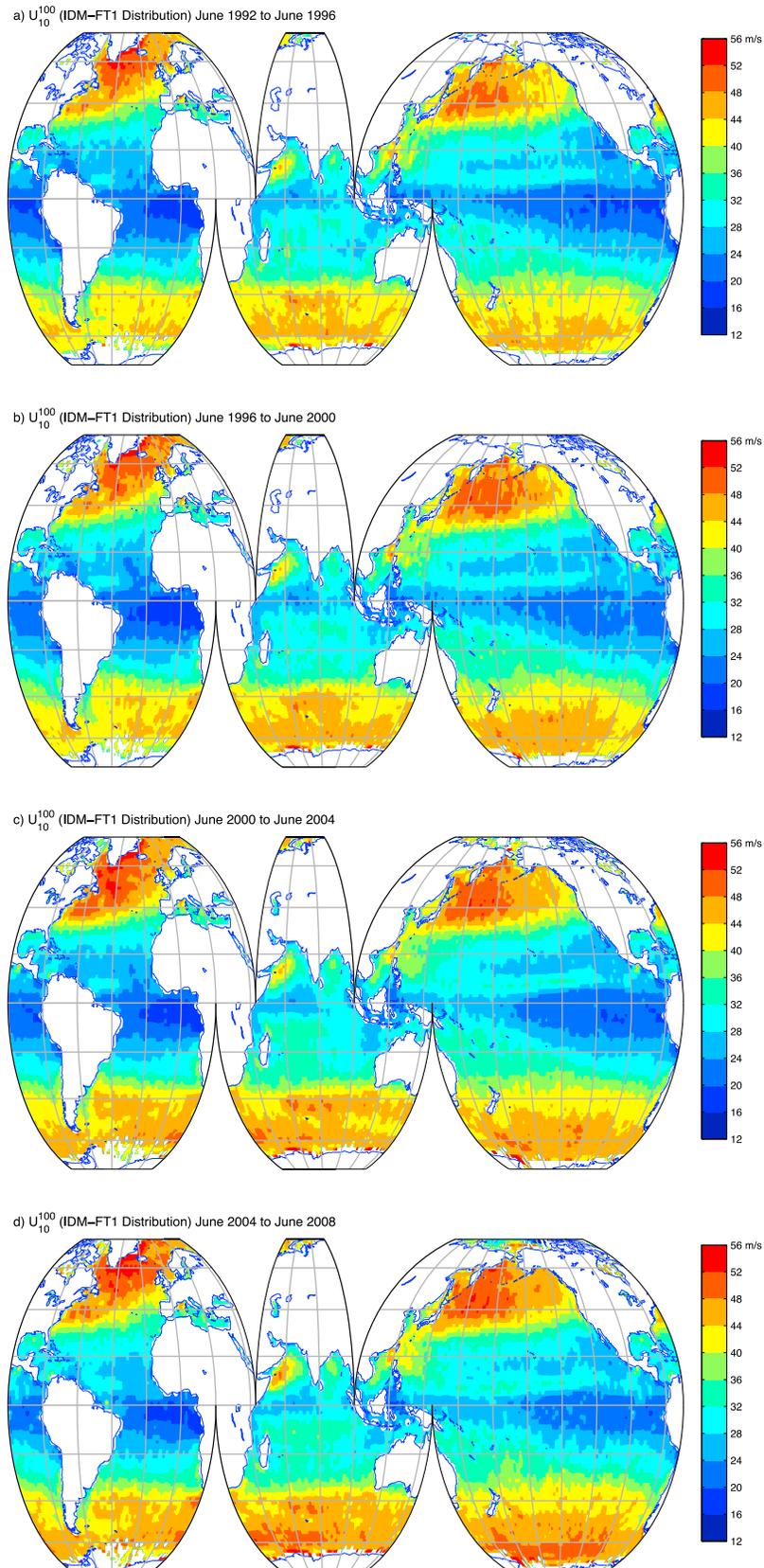
[38] The globe was first divided into  $2^0 \times 2^0$  bins and all altimeter data allocated to bins based on the latitude, longitude and time of the measurement [Vinoth and Young, 2011]. Following the approach adopted by *Caires and Sterl* [2005], the full data set is partitioned into time segments and the 100 year return period values of wind speed,  $U_{10}^{100}$  and significant wave height,  $H_s^{100}$  determined for each segment. In contrast to *Caires and Sterl* [2005], the IDM approach is used to determine return period values for each segment, rather than the POT approach. As shown by *Alves and Young* [2003] and *Vinoth and Young* [2011], the POT approach is impacted by undersampling, particularly when applied to altimeter data and requires long time series to produce reliable results. In contrast, the IDM approach is less sensitive to the length of the time series, a requirement in the present analysis, where relatively short subperiods of the full data set are to be analyzed.

[39] Variability in the estimates of the extreme value wind speed and wave height could be reduced by, for instance, considering 50 year return period events rather than 100 year estimates. As both previous extreme value trend studies [Caires and Sterl, 2005] and extreme value climatology studies [Vinoth and Young, 2011] have used the 100 year return period, this same value has been adopted here.

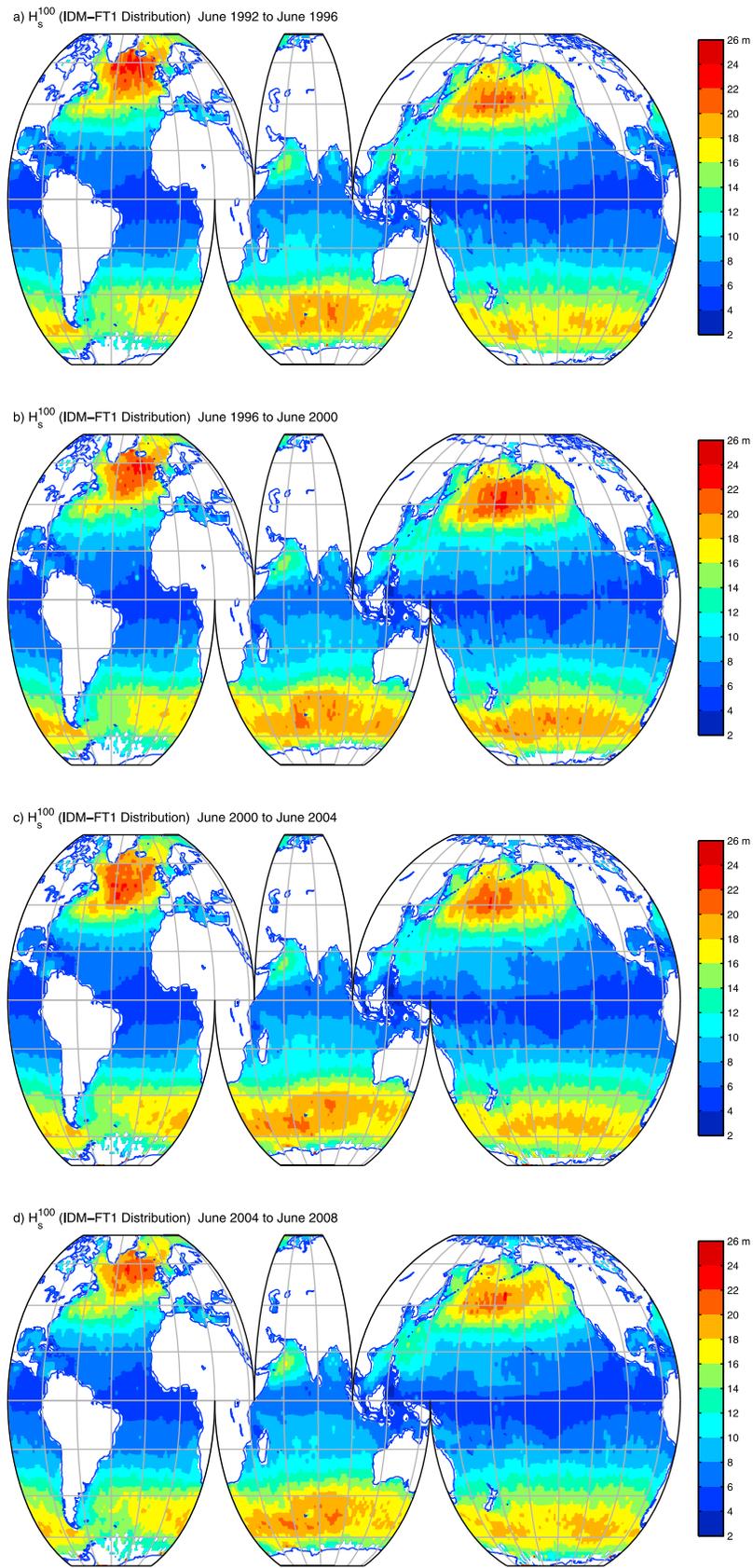
[40] Both 2 year and 4 year segments were investigated. The results were similar, although the 4 year estimates of the 100 year return period values (not surprisingly) appeared more stable. That is, both the spatial variation across the globe and changes from one segment to the next exhibited less variability. Nevertheless, results were similar and hence only 4 year segments are shown here.

[41] Figure 4 shows color contour plots of the global distribution of  $U_{10}^{100}$  calculated using the IDM and a FT-1 distribution for each subperiod (Figure 4a, 1992–1996; Figure 4b, 1996–2000; Figure 4c, 2000–2004; Figure 4d, 2004–2008). The figures reflect the same global trends reported by *Alves and Young* [2003], *Caires and Sterl* [2005], and *Vinoth and Young* [2011]. High values are found in the latitudes of  $40\text{--}50^\circ$  in both hemispheres, these values gradually decreasing toward the equator. In addition, localized features, such as the high winds associated with the Somali jet in the Arabian Sea are also evident. Visual inspection indicates that the wind speed appears to increase across the figures, particularly at the high latitudes of both hemispheres.

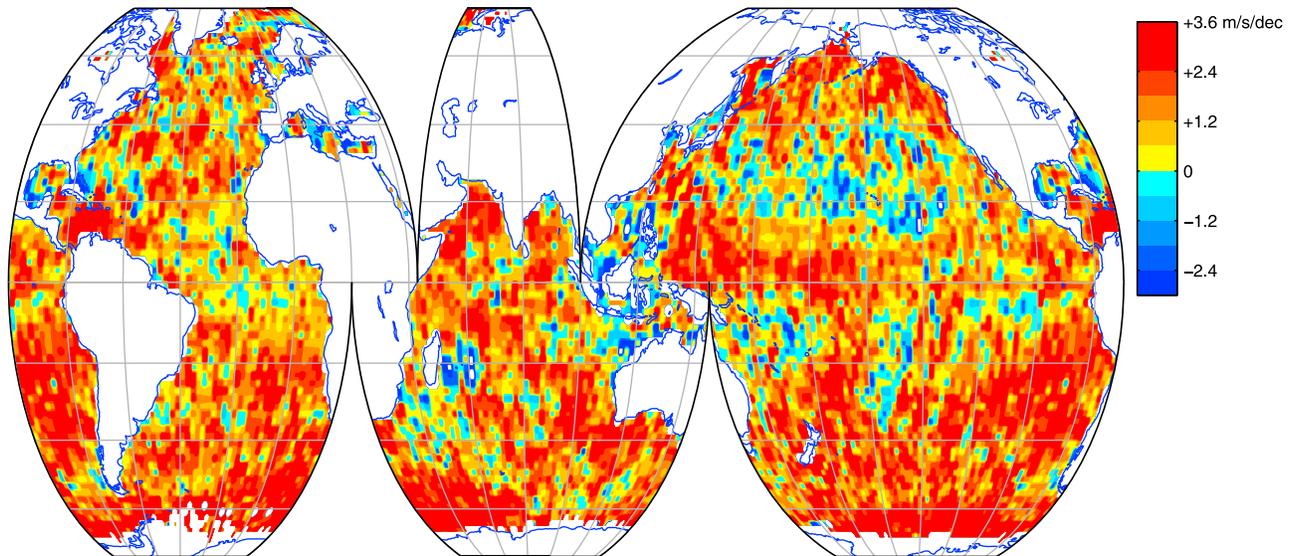
[42] Figure 5 shows the corresponding global distributions of  $H_s^{100}$  for each of the four periods. The spatial distributions are similar to those for wind speed. Visual inspection suggests there may be a small increase in  $H_s^{100}$  at high latitudes across the four periods, although this is much less clear than for wind speed.



**Figure 4.** The 100 year return period wind speed,  $U_{10}^{100}$ , determined using the IDM approach with an FT-1 distribution. The values calculated for different periods, (a) 1992–1996, (b) 1996–2000, (c) 2000–2004, and (d) 2004–2008, are shown.



**Figure 5.** The 100 year return period significant wave height,  $H_s^{100}$ , determined using the IDM approach with an FT-1 distribution. The values calculated for different periods, (a) 1992–1996, (b) 1996–2000, (c) 2000–2004, and (d) 2004–2008, are shown.

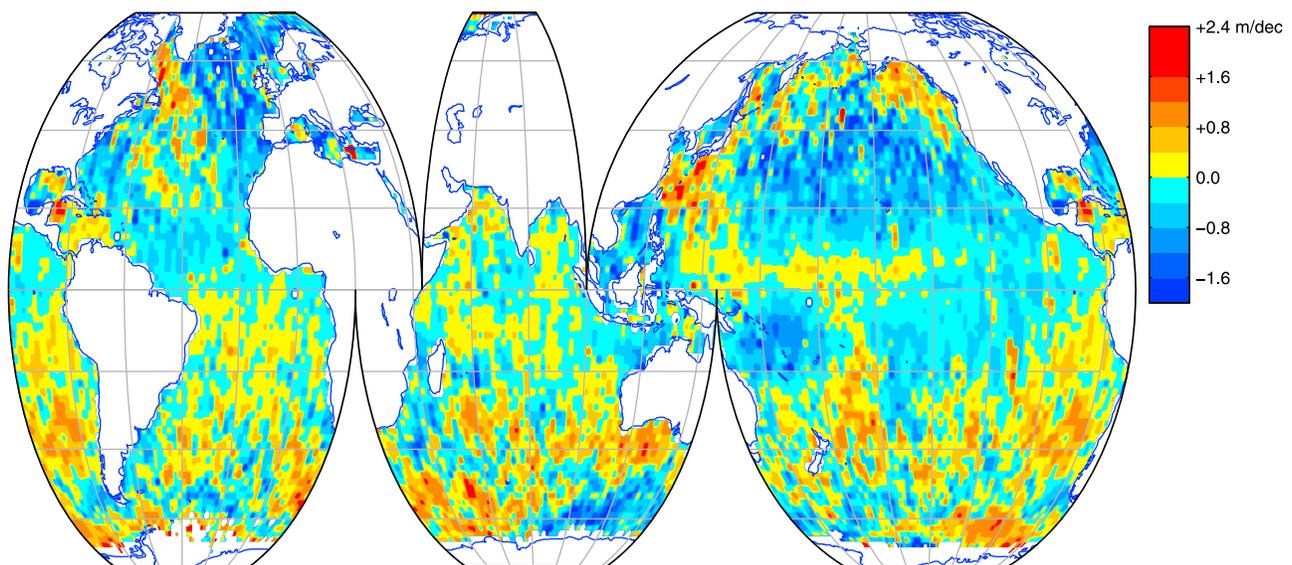


**Figure 6.** The trend in  $U_{10}^{100}$  calculated using linear regression from the extreme value analysis of the periods shown in Figure 4.

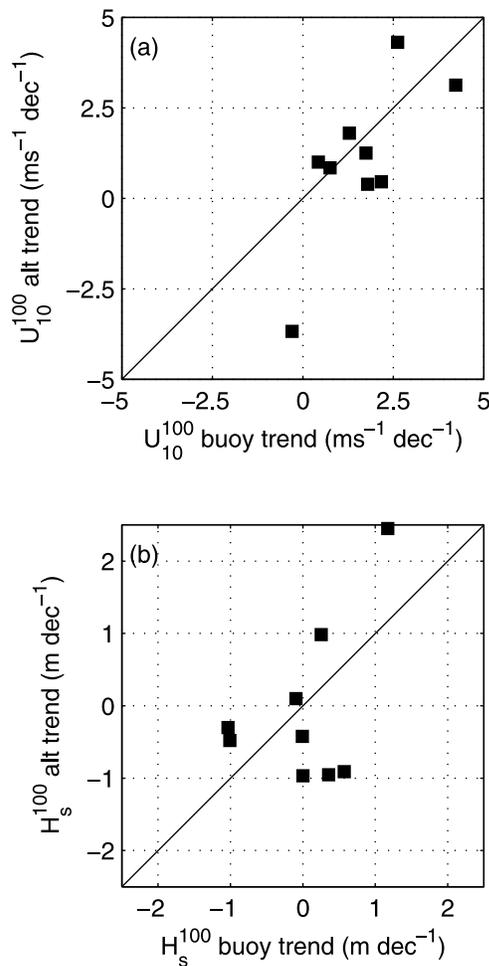
[43] Simple linear regression [Zieger, 2010] can be used to estimate the trend across the subintervals for both  $U_{10}^{100}$  and  $H_s^{100}$ . The resulting trends are shown for  $U_{10}^{100}$  in Figure 6 and for  $H_s^{100}$  in Figure 7. As shown below, because of the large confidence intervals associated with the individual estimates of the extreme values for each bin, the results, not surprisingly, exhibit statistical noise. Nevertheless, the wind speed (Figure 6) shows a consistent global positive trend (increasing values of extreme wind speeds). In contrast, the situation for wave height is much less clear. There is some suggestion that there are increasing wave heights in the Southern Ocean, but significant regions of the globe show weak negative trends (decreasing extreme wave heights).

[44] Limited long-term buoy data is available for validation purposes. *Vinoth and Young* [2011] used deep water

buoy data available from the U.S. National Oceanographic Data Center (NODC) [e.g., *Evans et al.*, 2003] to validate extreme value estimates. A limited number of these buoys were in long-term operation over the period of the altimeter data. The same analysis procedure (i.e., subdivision into 4 year blocks and IDM estimation) was used to determine the trend for this set of buoys. Comparisons between buoy and altimeter estimates of the  $U_{10}^{100}$  and  $H_s^{100}$  trends are shown in Figure 8. For both wind speed and wave height the buoy trends are consistent with the altimeter estimates. Again, as noted below, there is significant scatter about the 1:1 line. However, the buoy data shows a weak positive trend in  $U_{10}^{100}$  and no consistent trend in  $H_s^{100}$ . Because of the limited number of comparison buoys, it cannot be claimed that the



**Figure 7.** The trend in  $H_s^{100}$  calculated using linear regression from the extreme value analysis of the periods shown in Figure 5.

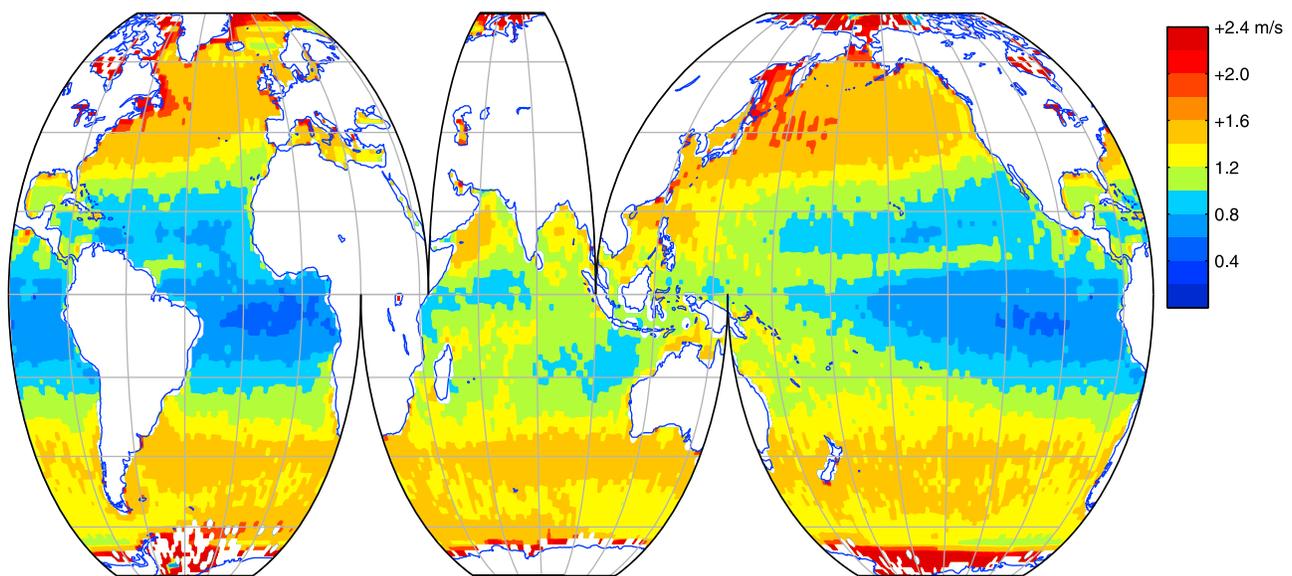


**Figure 8.** Comparison between trends in extreme values determined from NODC data buoys and altimeter data from  $2^\circ \times 2^\circ$  regions around each buoy. (a) Values for wind speed,  $U_{10}^{100}$ . (b) Values for significant wave height,  $H_s^{100}$ .

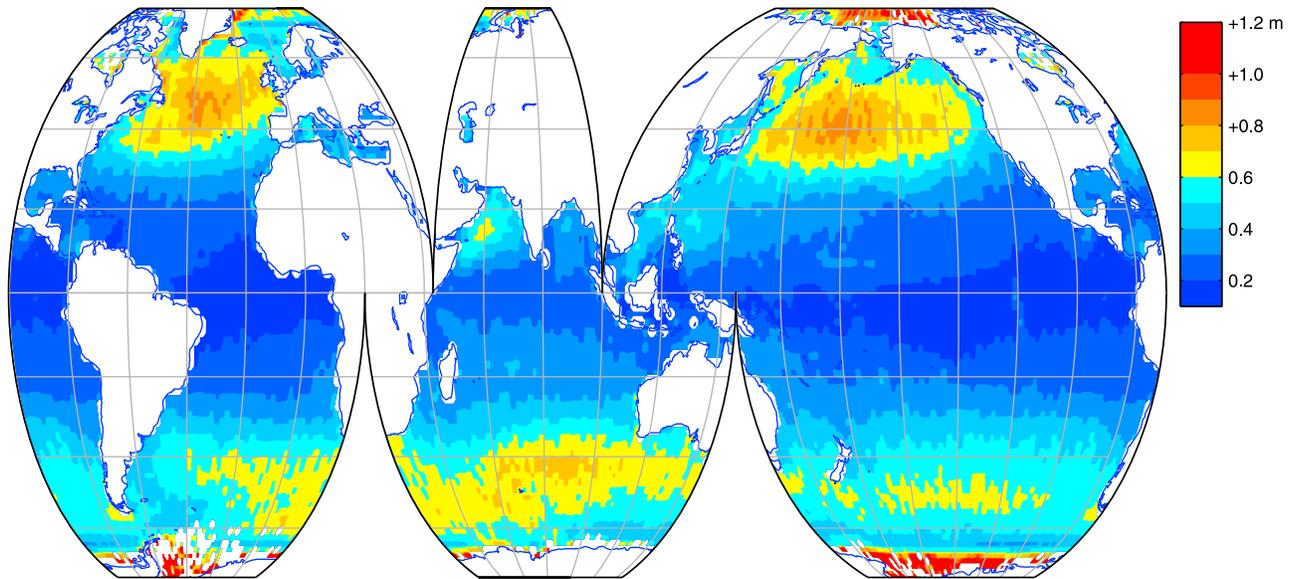
buoy data validates the altimeter estimates, only that the results are consistent.

[45] The length of the available time series (4 years in the present context), the frequency of the observations and the degree to which the data fit the assumed FT-1 probability distribution define confidence limits on the estimates of the 100 year return period values [Goda, 2000]. Figures 9 and 10 show the global distribution of the confidence interval,  $I_{100}$ , for each of  $U_{10}^{100}$  and  $H_s^{100}$ , respectively. The case shown in these figures is for the period 2000–2004. As the number of satellites in operation at any instant varied over the duration of the data set, the exact values of  $I_{100}$  were not uniform over the four subintervals. These figures are, however, representative. The 95% confidence limits are defined as  $\pm I_{100}$ . The values of  $I_{100}$  vary with the magnitude of  $U_{10}^{100}$  and  $H_s^{100}$ . For  $U_{10}^{100}$ , values range between  $0.6 \text{ ms}^{-1}$  and  $1.8 \text{ ms}^{-1}$  and for  $H_s^{100}$  between  $0.2 \text{ m}$  and  $0.8 \text{ m}$ . These intervals are of the same order of magnitude as the differences between the successive 4 year estimates of the 100 year return periods. Hence, determining trends from the differences between the estimates is challenging.

[46] Examination of Figures 9 and 10 shows that the confidence intervals on the individual values of  $U_{10}^{100}$  and  $H_s^{100}$  are large compared to the observed trends. For instance, typical values of the confidence limits from Figures 9 and 10 are:  $1.0 \text{ m/s}$  for  $U_{10}^{100}$  and  $0.5 \text{ m}$  for  $H_s^{100}$ . That is, this is the level of confidence in the individual points used to determine the trend. Figures 6 and 7 show typical trends of order  $1.2 \text{ ms}^{-1} \text{decade}^{-1}$  for  $U_{10}^{100}$  and  $\pm 0.8 \text{ m decade}^{-1}$  for  $H_s^{100}$ . Hence, the confidence limits on the individual data points are as large as the expected change over a 10 year period. Averaging over the entire globe will increase the statistical confidence in the trend estimates. The resulting global average  $U_{10}^{100}$  trend is  $0.68 \text{ ms}^{-1} \text{decade}^{-1}$  and the global average  $H_s^{100}$  trend is  $-0.38 \text{ m decade}^{-1}$ . These values confirm the visual observation that there is a positive trend in  $U_{10}^{100}$  and almost neutral conditions for  $H_s^{100}$ . Interestingly,



**Figure 9.** Values of the confidence interval on  $U_{10}^{100}$  calculated from the period 2000–2004. The method proposed by Goda [2000] was used to determine the confidence interval.



**Figure 10.** Values of the confidence interval on  $H_s^{100}$  calculated from the period 2000–2004. The method proposed by *Goda* [2000] was used to determine the confidence interval.

the value for  $U_{10}^{100}$  is comparable to the 99th percentile result reported by *Young et al.* [2011a].

## 6. Conclusions

[47] As noted in the literature review, there is growing evidence that over the past 25 years (and possibly longer) there has been a global increase in wind speed and possibly wave height. The evidence for an increase in wave height is weaker but one would infer that increasing wind speed must eventually be reflected in similar trends in wave height. There is also some evidence that extreme events may be increasing at a faster rate. Should such increases in extreme events be confirmed then this has significant impact on engineering design in both coastal and offshore areas with major impacts on safety, operability of shipping and structures and the economics of offshore facilities.

[48] The present analysis considers the long-duration (23 years) altimeter data set of *Zieger et al.* [2009], divides the time series into relatively short segments (4 years duration) and determines the 100 year return period wind speed and significant wave height for each segment. The trend in the values of the 100 year return period estimates is then examined across the duration of the total data record. The results are consistent with the limited buoy data and suggest that there is an increasing trend in  $U_{10}^{100}$  and no clear trend in  $H_s^{100}$ . The confidence limits associated with the estimates of both quantities for each of the 4 year periods are, however, large and hence the trend estimates are not considered quantitatively reliable. Hence, the analysis cannot reliably confirm the magnitudes of any trends.

[49] As winds generate waves, the apparent trend in wind speed but not in wave height needs to be understood. Altimeter measurements of wave height are more reliable than altimeter winds. Hence, some doubt could be raised over the validity of such wind measurements. However, observations of mean wind speeds consistently show positive trends from different instruments and different studies

(see Figure 2). This seems to support a positive trend in extreme wind speed. Wave height does not, however, depend solely on wind speed [*Young*, 1999]. The duration and fetch of the wind is also important. Mean and extreme winds could increase, but should they be less consistent in duration or direction, then the resulting wave height may not be significantly impacted. In order to investigate such effects a “basin by basin” analysis, investigating the duration and directional changes of wind fields is required. This would require information on wind and wave direction, as well as their magnitudes. Such information is not available from the altimeter or SSM/I data which have been previously used for such studies. Additional data sources and model studies would be required for such an analysis.

[50] One can speculate that, should the observed increasing trends in mean and percentile values of wind speed and wave height continue into the future, then this will also result in increased values of extreme value return period estimates. However, the available data set is still too short to obtain reliable return period trend estimates.

[51] In order to reduce the magnitude of the confidence limits for such an analysis, it will be necessary to increase the length of the analysis blocks (e.g., extend from 4 years to say 10 years) and also increase the number of such blocks. This suggests that a time series as long as 100 years may be required to address the problem. As this is much longer than the presently available global data sets (SSM/I and altimeter are approximately 25 years), it is likely that any estimates will need to rely on either reanalysis model data or model predictions of future climate scenarios. Although such an approach has the inherent limitations of the reliability of model physics and forcing, there seems no other practical approach to obtain information on these important environmental design parameters.

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